

CS 744: PIPE DREAM

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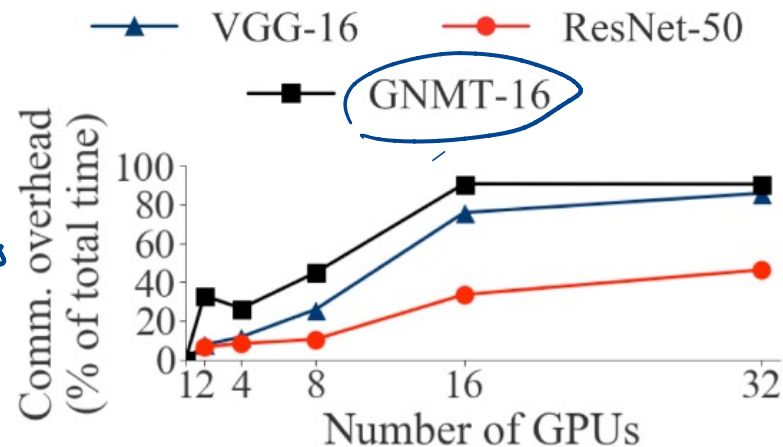
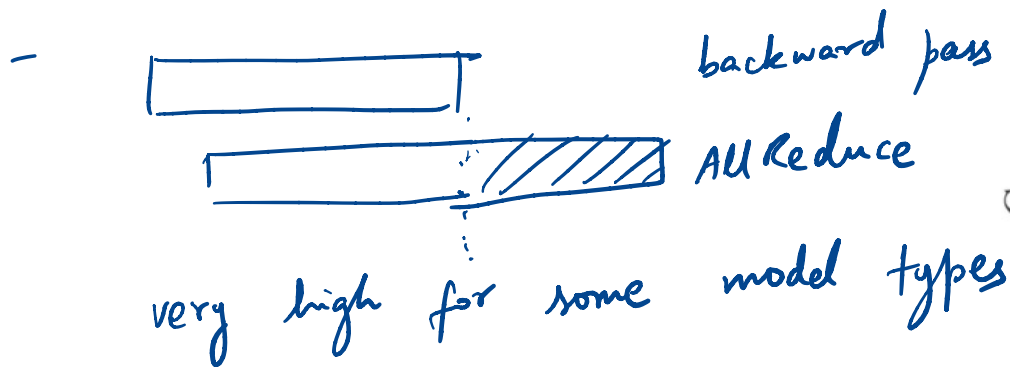
Fall 2022

ADMINISTRIVIA

- Assignment 2 is due Wednesday AM! → Please post on Piazza
- Course project preference sheet: Out today!
 - Propose your own?
 - Or rank 1 through 5 of some project ideas we have
 - Group!

LIMITATIONS OF DATA PARALLEL

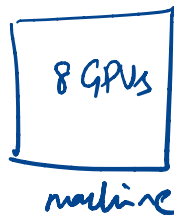
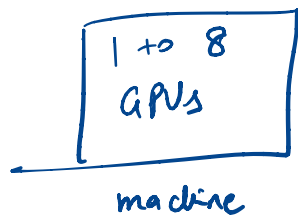
- Overhead increases as num GPUs increases



8xV100s with NVLink (AWS)
PyTorch + NCCL 2.4

5

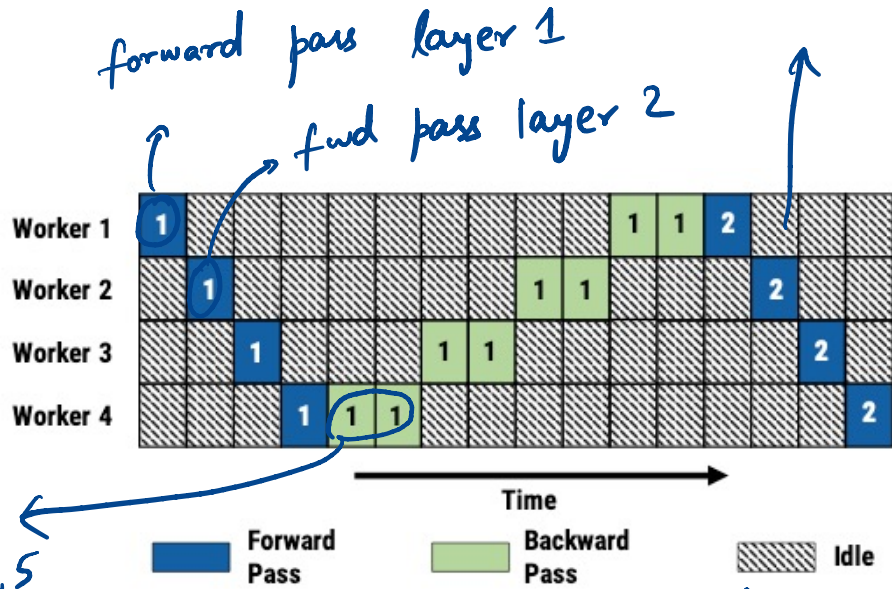
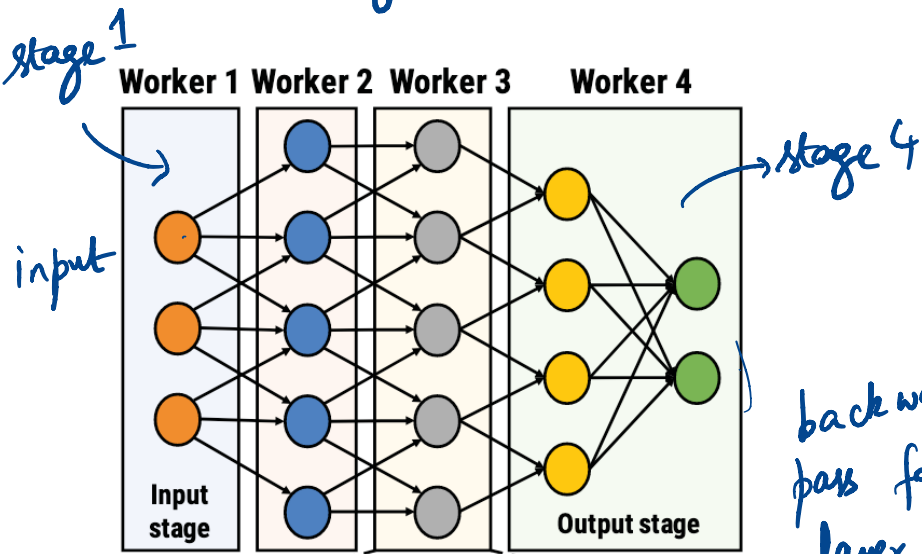
- Overhead is lower ≤ 8 GPUs, higher after that



“fraction of training time spent in communication stalls”

MODEL PARALLEL TRAINING

5 layers in model



backward pass for layer 4,5

gradients here

- ① Comm is constant
- ② Memory req. are lower & can use heterogeneous machines.

as num workers increases, limited connection

PIPELINE PARALLEL

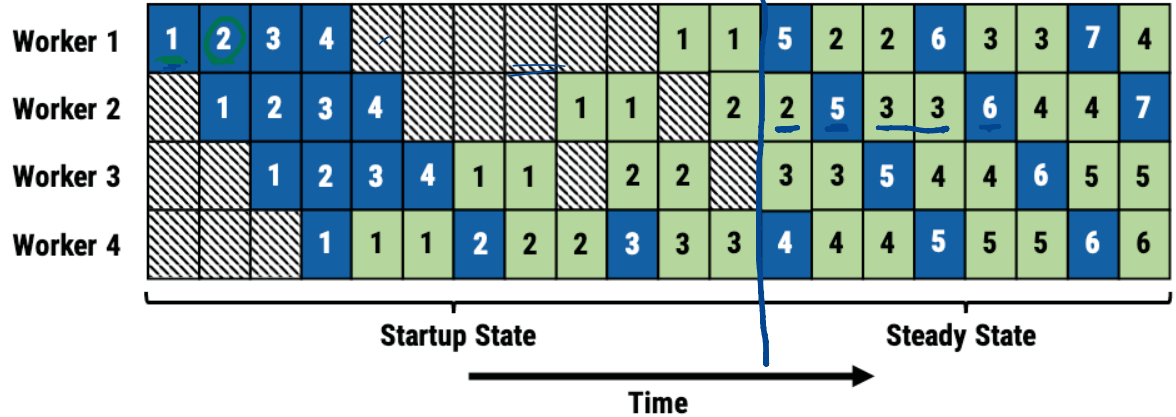
Key Idea:

Instead of 1 input batch
feed in "k" batches

- Handle scenarios
where some stages
are slow.

k = 4 here

steady state
util is high



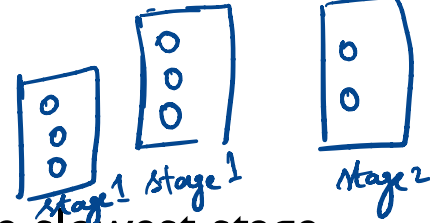
Advantages?

- fixed comm. overhead
- high utilization

- Partitioning
- Scheduling of FWD, BCKWD
- Learning

CHALLENGE 1: WORK PARTITIONING

similar time?

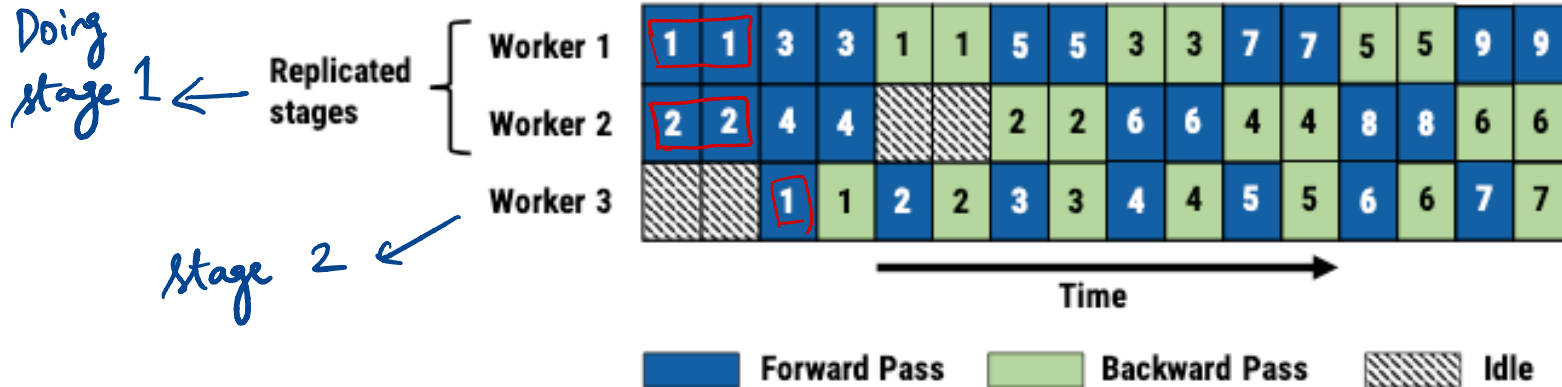


Goal: Balanced stages in the pipeline. Why?

Steady state throughput is the throughput of the slowest stage

→ *Hybrid parallel*

Stages can be **replicated**! Ex: Two stage pipeline, but first stage is replicated



WORK PARTITIONING

Profiler: computation time for forward, backward for each layer
size of output activations, gradients (network transfer)
size of parameters (memory)

Dynamic programming algorithm

Intuition: Find optimal partitions within a server,
Then find best split across servers using that

Given
- model
- cluster
↳ GPUs, network

Static plannings

CHALLENGE 2: WORK SCHEDULING

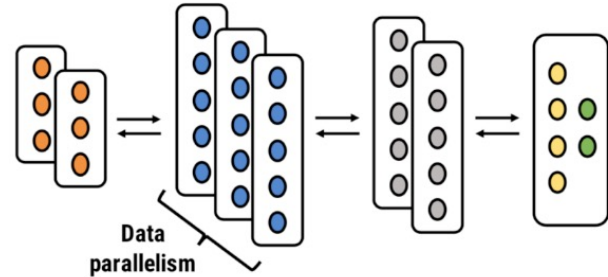
Traditional data parallel

forward iter(i) *Iteration 0*

backward iter(i)

forward iter(i+1) *Iteration 1*

...



Pipeline parallel: Worker can

Forward pass to push to downstream

Backward pass to push to upstream

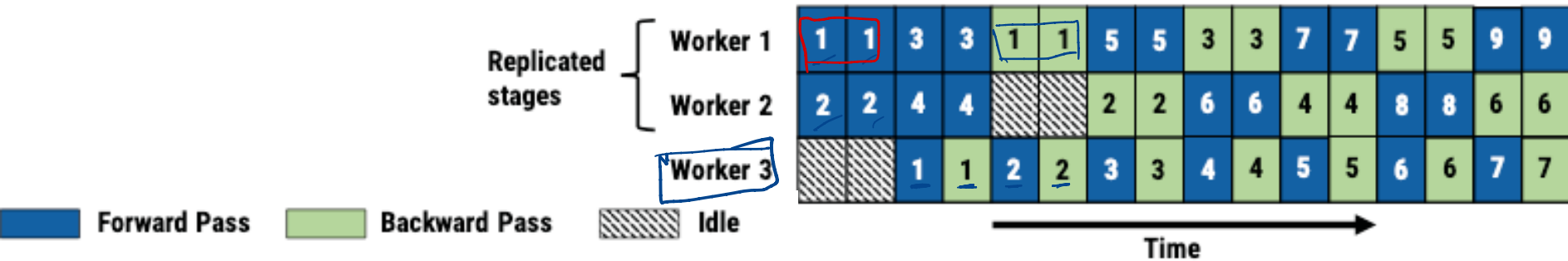
*either run fwd pass
next batch or
backward pass for
prior batch*

CHALLENGE 2: WORK SCHEDULING

Num active batches \approx num_workers / num_replicas_input

Schedule one-forward-one-backward (IFIB) – Worker 3 → makes sure pipeline is making progress

Round-robin for replicated stages → Worker 2
same worker for fwd, backward



CHALLENGE 3: EFFECTIVE LEARNING

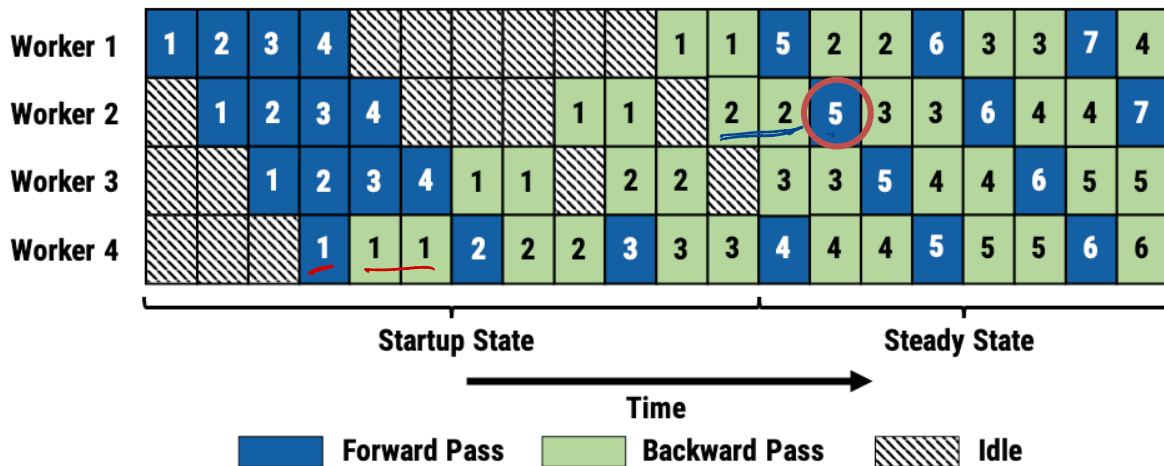
Naive pipelining

Different model versions forward and backward

Batch no. 5

↳ fwd pass uses model v2.

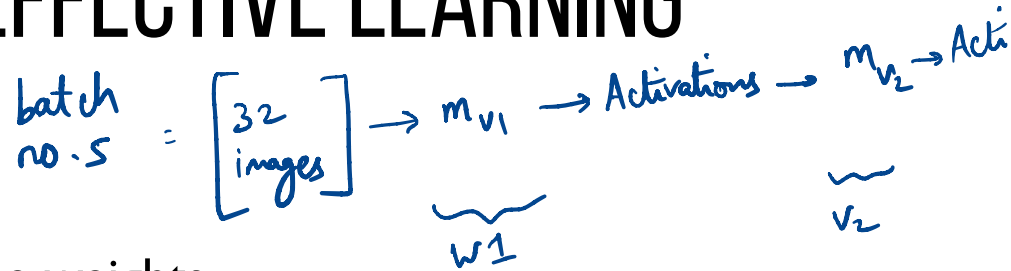
↳ bck pass used model v4.



Keep model v2 stashed

batch 5 ≡ v2

CHALLENGE 3: EFFECTIVE LEARNING



Weight stashing

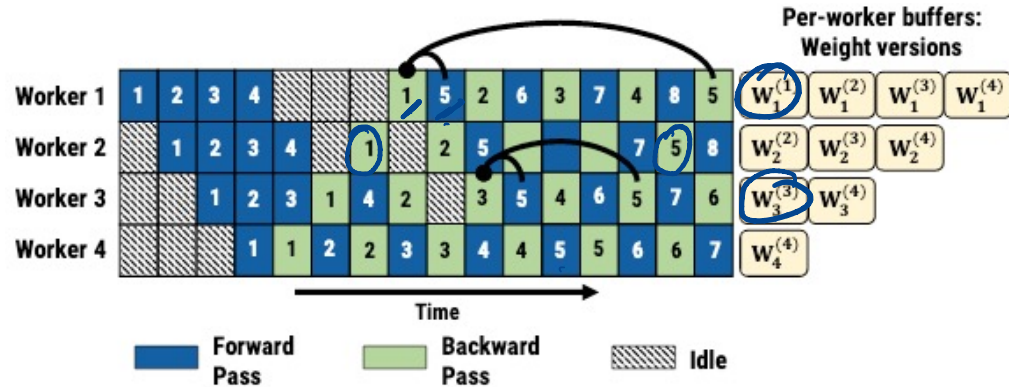
Maintain multiple versions of the weights

One per active mini-batch

Use latest version for forward pass.

Retrieve for backward

No guarantees across stages!



↳ diff model versions used in diff stages

STALENESS, MEMORY OVERHEAD

How to avoid staleness:

Vertical sync



in the first stage, record model version
propagate that across workers used

Memory overhead

Similar to data parallel?

↳ lose this benefit with vertical sync.

SUMMARY

Pipeline parallelism: Combine inter-batch and intra-batch

Partitioning: Replication, dynamic programming

Scheduling: IFIB

Weight management: Stashing, vertical sync

DISCUSSION

<https://forms.gle/5cfI6BWn6Dziey6e6>

Data parallel - not always bad

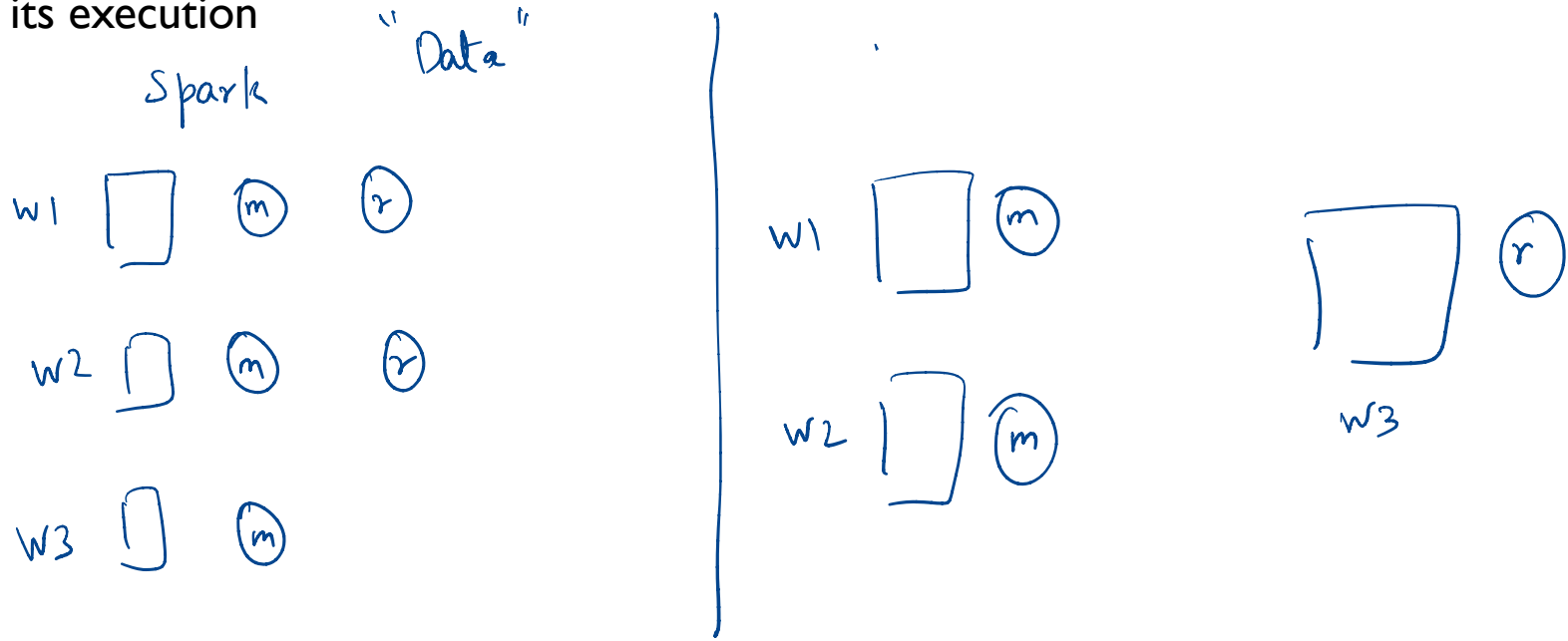
- speed up higher
vgg-16

4x4 → more overhead
List two takeaways from the following table
for data parallel

Model Name	Model Size	GPUs (#Servers x #GPUs/Server)	PipeDream Config	Speedup over DataParallel (Epoch Time)
Resnet-50	97MB	4x4 2x8	16 16	1x 1x
VGG-16	528MB	4x4 2x8	15-1 15-1	5.28x 2.98x
GNMT-8	1.1GB	3x4 2x8	Straight 16	2.95x 1x

why??

What are some other workload scenarios (e.g. things we discussed for MapReduce or Spark) that could use similar ideas of pipelined parallelism? Develop such one example and its execution



NEXT STEPS

Next class: Parameter Server

Assignment 2 is due soon!

Course project preference form out today!